

This article was downloaded by: [Cornell University Library]

On: 6 January 2010

Access details: Access Details: [subscription number 915425287]

Publisher Routledge

Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK



Biodemography and Social Biology

Publication details, including instructions for authors and subscription information:

<http://www.informaworld.com/smpp/title~content=t912661267>

Adding Biomeasures Relating to Fatness and Obesity to the Panel Study of Income Dynamics

Richard V. Burkhauser ^a; John Cawley ^a

^a Department of Policy Analysis and Management, Cornell University, Ithaca, New York, USA

Online publication date: 29 December 2009

To cite this Article Burkhauser, Richard V. and Cawley, John(2009) 'Adding Biomeasures Relating to Fatness and Obesity to the Panel Study of Income Dynamics', *Biodemography and Social Biology*, 55: 2, 118 — 139

To link to this Article: DOI: 10.1080/19485560903382395

URL: <http://dx.doi.org/10.1080/19485560903382395>

PLEASE SCROLL DOWN FOR ARTICLE

Full terms and conditions of use: <http://www.informaworld.com/terms-and-conditions-of-access.pdf>

This article may be used for research, teaching and private study purposes. Any substantial or systematic reproduction, re-distribution, re-selling, loan or sub-licensing, systematic supply or distribution in any form to anyone is expressly forbidden.

The publisher does not give any warranty express or implied or make any representation that the contents will be complete or accurate or up to date. The accuracy of any instructions, formulae and drug doses should be independently verified with primary sources. The publisher shall not be liable for any loss, actions, claims, proceedings, demand or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.

Adding Biomeasures Relating to Fatness and Obesity to the Panel Study of Income Dynamics

RICHARD V. BURKHAUSER AND JOHN CAWLEY

Department of Policy Analysis and Management, Cornell University,
Ithaca, New York

The pace of research on the causes and consequences of obesity has increased dramatically since the late 1990s. However, a great chasm exists between the high-quality measurements of fatness used in the medical literature and the mostly self-reported height and weight data found in social science surveys. This article discusses the scientific value of including more accurate measures of fatness in the Panel Study of Income Dynamics (PSID). It describes why fatness and obesity are of interest to PSID users, the concepts they measure, the strengths and weaknesses of alternative biomeasures for these concepts, the value added of including each in the PSID, and their synergies with the PSID structure. Although no single measure of fatness is ideal for every situation, given scarce PSID resources we recommend adding waist circumference, percentage of body fat, total body fat, and fat free mass through a method such as bioelectrical impedance analysis, as well as determining genetic predisposition to obesity.

Introduction

Obesity has more than doubled in the United States since 1980 (Hedley, Ogden, Johnson, Carroll, Curtin, and Flegal 2004; Ogden, Carroll, Curtin, McDowell, Tabak, and Flegal 2006), and research on its causes and consequences, both in the medical and social science literatures, has risen dramatically since the late 1990s. However, a great chasm exists between the high-quality measurements of fatness used in the medical literature and the mostly self-reported information on height and weight contained in data sets used by social scientists. The result has been that researchers interested in linking fatness to social science issues—employment, wages, discrimination, child development, marriage, welfare or social insurance program participation, etc.—have been forced to use either medically based surveys with very limited information on these outcomes or social science surveys containing, at best, self-reported height and weight. Neither of these strategies is optimal.

This article argues that there are substantial benefits to including accurate measures of fatness in existing social science surveys, and that the costs of doing so have declined sufficiently that it is now feasible to add such measures to social science surveys in general and to the Panel Study of Income Dynamics (PSID) in particular. This article first describes why fatness and obesity are of interest to PSID users. It then reviews the

The authors thank Jeff Larrimore for research assistance and the following individuals for their helpful comments: Robert F. Schoeni, Narayan Sastry, Kate McGonagle, two anonymous referees, and participants in the conference “The Scientific Assessment of Biomeasures in the Panel Study of Income Dynamics” held in Ann Arbor, Michigan, on December 10–11, 2008.

Address correspondence to John Cawley, Department of Policy Analysis and Management, Cornell University, 125 Martha Van Rensselaer Hall, Ithaca, NY 14853-4401. E-mail: JHC38@cornell.edu

concepts one could measure and the strengths and weaknesses of specific ways of measuring those concepts. The article then discusses the overall value added of including each of these biomeasures in the PSID and their synergies with the PSID structure. Although no single fatness measure is ideal for every situation, given scarce PSID resources, we recommend focusing on adding waist circumference, percentage of body fat, total body fat, and fat free mass, as well as determining genetic predisposition to obesity.

Why Fatness and Obesity Are of Interest to PSID Users

A wide variety of social science outcomes are affected by health (Culyer and Newhouse 2000), and one important dimension of health is fatness (adiposity). Fatness is a concept that refers to the abundance of adipose tissue, in which energy is stored in the form of fat cells (Bjorntorp 2002). Obesity is defined as excessive fatness (Bjorntorp; Bray, Bouchard, and James 1998).

Fatness and obesity are risk factors for mortality (Yusuf, Hawken, Ounpuu, et al. 2005; Pischon, Boeing, Hoffman, et al. 2008), especially from cardiovascular disease but also from cancer and other causes (Flegal, Gaubard, Williamson, and Gail 2007). Fatness and obesity are risk factors for specific morbid conditions, including ischemic heart disease, congestive heart failure, stroke, cancer, respiratory disease, diabetes, hyperlipidemia, hypertension, asthma, sleep apnea, arthritis, degenerative joint disease, gastric reflux, and depression (National Institutes of Health [NIH] 1998; U.S. Department of Health and Human Services [DHHS] 2001; Pi-Sunyer 2002). Given these associations, health care costs rise with weight (Pronk, Goodman, O'Connor, and Martinson 1999; Raebel, Malone, Conner, Xu, Porter, and Lanty 2004; Wang, McDonald, Bender, Reffitt et al. 2006). The costs of treating obesity-related illnesses in the United States is estimated to be \$93 billion annually (Finkelstein, Fiebelkorn, and Wang 2003).

The doubling of the prevalence of obesity in the United States since 1980 (Hedley et al. 2004; Ogden, Carroll, Curtin, McDowell, Tabak, and Flegal 2006; Burkhauser, Cawley, and Schmeiser 2009) is one of the most dramatic public health trends in American history. Obesity is now one of the most serious public health challenges facing the United States (U.S. DHHS 2001).

Obesity is of tremendous interest to social scientists because of its correlation with demographic factors as well as social and economic outcomes. For example, there are stark differences in obesity across race and ethnic groups by gender. Table 1 shows the prevalence of overweight, obesity and extreme obesity, based on the body mass index (BMI),¹ in the United States during 2003–2004 among adults aged 20 years and older, by gender and race/ethnicity (Ogden et al. 2006). For each race/ethnic group, extreme obesity is at least twice as high among women as men. Though there is little difference in the prevalence of obesity among men of different race/ethnic groups (31–34%), there is considerable difference in the prevalence of obesity among women of different race/ethnic groups; it equals 30.2 percent for non-Hispanic white females, 42.3 percent for Mexican American females, and 53.9 percent non-Hispanic black females. Thus, obesity is of considerable interest to researchers studying gender, race, and ethnicity.

Labor and health economists have documented a number of important associations between obesity and labor market outcomes. A robust finding across a large number of

¹BMI is equal to weight in kilograms divided by height in meters squared. Heymsfield, Shen, Wang, et al. (1998) discuss the literature on weight-height indices that raise the denominator to powers other than 2.

Table 1
Prevalence of obesity, United States 2003–2004

	Percent Overweight (BMI ≥ 25)	Percent Obesity (BMI ≥ 30)	Percent Extreme obesity (BMI ≥ 40)
Non-Hispanic white males	70.6	31.1	2.8
Non-Hispanic white females	58.0	30.2	5.8
Non-Hispanic black males	69.1	34.0	5.4
Non-Hispanic black females	81.6	53.9	14.7
Mexican American males	76.1	31.6	1.7
Mexican American females	75.4	42.3	7.8

Source: Ogden et al. (2006).
Notes: Prevalence of obesity (BMI = body mass index) for adults aged 20 years or older in 2003–2004.

studies is that obese individuals (in particular, obese women) tend to earn less (Taubman 1975; McLean and Moon 1980; Register and Williams 1990; Loh 1993; Averett and Korenman 1996, 1999; Pagan and Davila 1997; Haskins and Ransford 1999; Cawley 2004; Cawley, Grabka, and Lillard 2005; Conley and Glauber 2007; Kline and Tobias 2008). Moreover, there is evidence that the relationship is causal—that obesity lowers wages for women (Cawley; Kline and Tobias).

In addition, many studies have found that obesity is associated with a lower probability of employment (e.g., Sarlio-Lahteenkorva and Lahelma 1999; Cawley and Danziger 2005; Paraponaris, Saliba, and Venelou 2005; Tunceli, Li, and Williams 2006; Garcia and Quintana-Domeque 2007; Lundborg, Bolin, Johgard, and Lindgren 2007; Morris 2007; Burkhauser and Cawley 2008; Han, Norton and Stearns 2009; Johansson et al. 2009). Obesity is also associated with a higher probability of work limitations or disability (e.g., Narbro et al. 1999; Cawley 2000; Ferraro et al. 2002; D. N. Lakdawalla, Bhattacharya, and Goldman 2004; Okoro, Hootman, Strine, Balluz, and Mokdad 2004; Sturm, Ringel, and Andreyeva 2004; Tunceli et al. 2006; Snih, Ottenbacher, Markides, Kuo, Eschbach, and Goodwin 2007; Burkhauser, Cawley, and Schmeiser 2008) and higher job absenteeism (Cawley, Rizzo, and Haas, 2007; Finkelstein, Fiebelkorn, and Wang 2005).

Researchers have concluded that “The stigmatization directed at obese children, by their peers, parents, educators, and others is pervasive and often unrelenting” (R. M. Puhl and Latner 2007:574). There is equally strong evidence of discrimination against obese adults; research has documented weight-based discrimination at every stage of employment, from the hiring decision through wage-setting and promotion (Roehling 1999; R. Puhl and Brownell 2001). Roehling even found that weight explains a greater proportion of the variance in hiring decisions than race or gender. In a recent survey, 12.2 percent of all U.S. adults (not just obese adults, but all adults) reported being discriminated against because of their weight or height, with an average of 4.9 lifetime experiences of such discrimination (Andreyeva, Puhl, and Brownell 2008). In general, the social stigma of obesity is greater for women than for men (Sobal 2004). For example, obesity has been shown to be associated with a lower probability of dating for teenage girls (e.g., Cawley, Joyner, and Sobal 2006), a lower probability of matching with a physically attractive partner (e.g., Carmalt, Cawley, Joyner, and Sobal 2008),

and a lower probability of marriage for adult women (e.g., Averett and Korenman 1999).

Despite the paucity of information about fatness and obesity in the PSID, that data set has been used to study a host of questions regarding obesity; e.g., the impact of grandparental and parental obesity on childhood overweight (Davis, McGonagle, Schoeni, and Stafford 2008), the link between obesity and labor market outcomes (Cawley et al. 2005; Tunceli et al. 2006; Conley and Glauber 2007), the link between maternal employment and childhood obesity (Fertig, Glomm, and Tchernis 2009), the link between preschool child care and childhood obesity (Lumeng, Gannon, Appugliese, Cabral, and Zuckerman 2005), and the association between food stamp receipt and obesity (Jones and Frongillo 2006).

In general, there has been a dramatic rise in the study of obesity in the past decade. Figure 1 depicts, for various databases of journal publications, the number of articles per year in which *overweight*, *obese*, or *obesity* appeared as a keyword or in the abstract. The left-hand scaling of the vertical axis applies to EconLit, an index of economics journals, Sociological Abstracts (SocAbstracts), and the Education Resource Information Center (ERIC), which covers education journals. The right-hand scaling of the vertical axis applies to MedLine, an index of medical and other life science journals. In each of these publication indices, the number of articles on obesity published annually has increased many times over during in the past decade.

In brief, fatness and obesity are of great interest to social scientists and others studying health, labor markets, discrimination, child development, marriage, and many other topics.

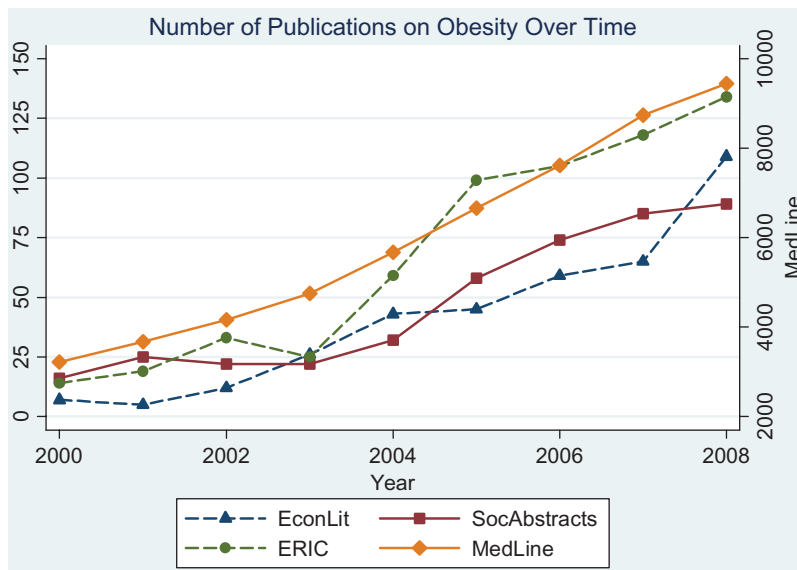


Figure 1. Number of published journal articles on obesity, by year and type of journal.

Notes: this graph shows the number of articles per year in which *overweight*, *obese*, or *obesity* appeared as a keyword or in the abstract for the following types of journals: economics journals (EconLit), sociology journals (SocAbstracts), education journals (ERIC), and medical and life science journals (MedLine). The left scaling of the vertical axis (i.e., 0 to 150) applies to EconLit, SocAbstracts, and ERIC. The right scaling of the vertical axis (i.e., 2,000 to 10,000) applies to MedLine.

Concepts of Fatness and Obesity That May Be Useful to Measure

There are a large number of ways to measure fatness and obesity. In the social science literature to date, fatness has almost universally been measured using BMI, which is equal to weight in kilograms divided by height in meters squared (NIH 1998; U.S. DHHS 2001). The advantage of BMI is that the information required to calculate it (weight and height) is easy to collect and relatively common in social science surveys such as the PSID, National Longitudinal Surveys of Youth (NLSY), Health and Retirement Study (HRS), Behavioral Risk Factor Surveillance System (BRFSS), National Health Interview Survey (NHIS), and National Longitudinal Survey of Adolescent Health (Add Health).

Despite the widespread use of BMI among social scientists, within the medical literature BMI is considered to be a noisy measure of fatness and obesity because it does not distinguish body composition; i.e., it does not distinguish fat from muscle, bone, and other lean body mass (Garn, Leonard, and Hawthorne 1986; Smalley, Knerr, Kendrick, Colliver, and Owen 1990; Gallagher, Visser, Sepulveda et al. 1996; Yusuf et al. 2005; McCarthy, Cole, Fry, Jebb, and Prentice 2006). As a result, BMI overestimates fatness among those who are muscular (Prentice and Jebb 2001; U.S. DHHS 2001).

Though there is consensus in the medical literature that BMI is a poor measure of fatness (Garn et al. 1986; Smalley et al. 1990; Gallagher et al. 1996; Yusuf et al. 2005; McCarthy et al. 2006), there is no consensus on which of the more accurate measures of fatness is best (Freedman and Perry 2000; Bouchard 2007). Candidates include total body fat (TBF); percentage of body fat (PBF), which is total body fat divided by total mass; waist circumference (WC); and waist-to-hip ratio (WHR). Each of these measures has its unique strengths and weaknesses. Fat causes Type II diabetes and cardiovascular disease by secreting resistin and leptin (Trayhurn and Beattie 2001), which suggests that total body fat may be the most relevant measure of fatness for predicting social science outcomes affected by health because the sheer volume of fat may determine the amount of leptin and resistin released. On the other hand, percentage of body fat may be a better predictor of health if additional fat free mass can dilute the health impacts of those secretions. Alternatively, if the outcome studied relates to appearance, waist-to-hip ratio may be most relevant (Singh and Young 1995; Braun and Bryan 2006).

There are a variety of definitions of obesity, corresponding to the various measures of fatness, and the strengths and weaknesses of each definition of obesity depends on the strengths and weaknesses of the measure of fatness on which it is based.² The most common measure of fatness is BMI, so it follows that the most common measure of obesity is based on BMI; specifically, a BMI of 30 or higher. The measure of obesity based on BMI suffers the same limitation as BMI itself: it ignores body composition. Medical researchers have concluded that the ability of BMI in particular, and weight-height indices in general, to identify true obesity (defined using direct measures of fatness) is “poor” (Smalley et al. 1990:408). Moreover, the inferiority of BMI at predicting health outcomes relative to more accurate measures of fatness led a 2005 editorial in the British medical journal *The Lancet* to conclude “. . . current practice with body-mass index as the measure of obesity is obsolete, and results in considerable underestimation of the grave consequences of the overweight epidemic” (Kragelund and Omland 2005:1590). An alternative is to define

²Whether one should model outcomes as a function of a continuous measure of fatness or a binary measure of obesity (and/or other weight classifications) depends on whether the outcome is linear or nonlinear over fatness. An intriguing question for future research is what the thresholds for clinical weight classification should be if they were to be based on social science outcomes instead of health outcomes.

obesity using percentage of body fat: the NIH states that individuals can be classified as obese if their percentage of body fat exceeds 25 percent for men or 30 percent for women (National Institute of Diabetes and Digestive and Kidney Diseases [NIDDK] 2006).

Findings from the medical literature also suggest that it is not just the amount of fat that matters but the location or distribution of that fat. In particular, abdominal visceral fat (i.e., that located around the internal organs) is associated with an elevated risk of morbidity (Bray et al. 1998). The amount of abdominal fat can be assessed using either waist circumference or waist-to-hip ratio; comparisons have found that these two are highly correlated with abdominal fat (Snijder, Visser, Dekker, et al. 2002).

The NIH classifies individuals at “high risk” if waist circumference exceeds 102 cm (40 inches) for men or 88 cm (35 inches) for women (NIH, 1998). If one is using waist-to-hip ratio as a measure of fatness, men are classified as high risk if their WHR is greater than 0.9 and women are classified as high risk if their WHR is greater than 0.8 (Dobbelsteyn, Joffres, MacLean, and Flowerdew 2001).

Bouchard (2007) wrote

Defining obesity and how to measure it is of paramount importance if we are to develop well-defined and evidence-based prevention and treatment programs. Unfortunately, there is a great deal of confusion at the moment regarding . . . what is the essence of obesity and what should be measured The view that excess body mass, as assessed by BMI, is inadequate and that excess fat mass (FM) would be a better indicator of obesity is commonly held. Others favor abdominal obesity as evaluated by waist girth as an even better obesity metric. Finally, some promote the notion that abdominal visceral fat (AVF) is all that matters in obesity. All of this is very confusing. (p. 1552)

Until recently the cost of collecting both measurements of fatness and in-depth social science outcomes in one survey was prohibitive. As a result, medical surveys that include direct measures of fatness tend to contain few outcomes of interest to social scientists, and social science surveys tend not to contain accurate measures of fatness such as TBF, PBF, WC, or WHR. However, the cost of devices to measure fatness directly has declined, and awareness has risen of the advantages of more accurate measures of fatness, making it both lower cost and more beneficial for social science surveys to include more accurate measures of fatness.

Biomeasures of Fatness and Obesity

In this section we describe the methods available for measuring each of the concepts described above.³ This discussion is limited to existing technology; as technological

³Estimates of body fat also depend on how many “compartments” (or categories) the masses of the body are assigned to. Typical models are: the two-compartment model (total body fat and fat-free mass [FFM]), the three-compartment model (total body fat, total body water, dry FFM), and the four-compartment model (total body fat, total body water, bone mineral mass, residual). Withers et al. (1998) found that the three-compartment is significantly more accurate than the two-compartment model, but the four-compartment model is not much more accurate than the three-compartment model. Heymsfield, Baumgartner, Allison, et al. (2004) noted that models with three or more compartments may yield more accurate estimates of body fatness, but any gain in accuracy could be swamped by increased errors of additional measurements, and any increased accuracy may not be worth the increased cost of obtaining additional measurements.

progress continues, the absolute and relative accuracy and cost of the various methods will likely change, implying that there is no single method that will always be the most accurate and cost effective. Those planning to add biomeasures to social science surveys are encouraged to seek out devices and even overall methods that may not have existed at the time of this writing. Moreover, over time there will exist a tradeoff between consistency (ensured by using the same devices wave after wave) and accuracy (upgrading to the latest and most accurate device available for each wave). It may be worth considering including some simple nontechnical measures such as waist circumference and body mass index in every wave to ensure comparability over time while also including in the portfolio higher-technology devices that measure body composition and whose accuracy is expected to improve over time.

For the devices described in this section, additional detail is available from the authors in an Excel file that has a different worksheet for each method of measuring fatness. For each device we list manufacturer, specifications, prices, and Web site links for more information. Upon request, we can also send user manuals for the devices. For more information on the methods of collecting each measure of fatness, and the strengths and weaknesses of each, see reviews by Heymsfield et al. (1998, 2004).

Body Mass

The standard measure of body mass is body mass index, which is a measure of weight for height. Ideally this is calculated using measured (as opposed to self-reported) weight and height. The accompanying worksheet lists three options for scales for measuring weight. Each scale measures weight to the nearest 0.2 pounds, and the maximum weight measurable ranges from 440 to 600 pounds. They range in price from \$169 to \$400. The National Health and Nutrition Examination Survey (NHANES) survey uses a Toledo brand scale.

The PSID collected self-reported weight and self-reported height in 1986 and 1999–2009. It has long been recognized that self-reports of weight and height are greatly inferior to their measured values for research purposes. For example, a 1992 meta-analysis concluded: “Caution is warranted if it is necessary to use self-reported values. It would be wise to use measured weights if the subjects are available, even if research expenses would be increased” (Bowman and DeLucia 1992, p. 637).

There is substantial reporting error in self-reports of weight (e.g., Rowland 1989); in general, the direction of reporting bias is negatively correlated with actual weight: underweight people tend to overreport their weight, and overweight people tend to underreport their weight. In the NHANES III, 21.8 percent of women misreported their weight by more than 4 kg or 8.8 pounds (Engstrom, Paterson, Doherty, Trabulsi, and Speer 2003). This reporting error can result in severe underestimates of the number of individuals in high weight classifications; for example, Nieto-Garcia, Bush, and Keyl (1990) documented that BMI calculated using self-reported weight and height correctly classifies only 74 percent of the truly obese (based on BMI calculated using measured weight and height). A review of the literature on misreporting of weight and height concluded that: “These findings indicate that self-reported height and weight measurements are not sufficiently accurate for use in clinical practice and clinically related research. Indeed, investigators of many of these studies recommended that height and weight be measured rather than self-reported whenever possible” (Engstrom et al., p. 343).

Reporting error in weight and height (and, therefore, BMI) may bias coefficient estimates (Bound, Brown, and Mathiowetz 2002). In the absence of measured values we (Cawley 2000, 2004) have used the self-reported values after applying the method for correcting reporting error recommended by Lee and Sepanski (1995) and Bound et al. Specifically, measured weight (height) was regressed on reported weight (height) in the NHANES and the coefficients were transported to a different survey that included reported but lacked measured values (e.g., PSID, NLSY); the NHANES coefficients were then multiplied by the reported values to get estimates of weight and height corrected for reporting error. However, this correction does not completely eliminate reporting error (Plankey, Stevens, Flegal, and Rust 1997), so measured weight is still preferable.

Digital scales are generally accurate to 0.2 pounds, so concerns about the reliability of measured weight have to do with, for example, the amount of clothing worn (which may vary seasonally). In collecting measured weights, NHANES uses the following procedures to maximize accuracy. Respondents are requested to wear a medical gown with only underwear beneath; if they do not wear the gown, respondents are coded as wearing clothing during the weighing. (There is also a special code for whether the respondent had a cast or prosthetic limb.) The NHANES is firm that respondents must not wear shoes during the weighing; any weighing during which the respondent wore shoes is considered invalid.

In the remainder of this article, comparisons of BMI to more accurate measures of fatness refer to BMI calculated from measured weight and height unless otherwise specified.

Central Adiposity

There are two standard measures of central adiposity: waist circumference and waist-to-hip ratio (which is the ratio of waist circumference to hip circumference). Both are assessed using a tape measure that does not stretch. Following are the instructions from NHANES for measuring waist circumference:

To define the level at which waist circumference is measured, a bony landmark is first located and marked. The subject stands and the examiner, positioned at the right of the subject, palpates the upper hip bone to locate the right iliac crest. Just above the uppermost lateral border of the right iliac crest, a horizontal mark is drawn, then crossed with a vertical mark on the midaxillary line. The measuring tape is placed in a horizontal plane around the abdomen at the level of this marked point on the right side of the trunk. The plane of the tape is parallel to the floor and the tape is snug, but does not compress the skin. The measurement is made at a normal minimal respiration. (NIH 1998, p. 58)

Relative to weighing someone, a complication of measuring waist and hip circumference is that it requires the examiner to have physical contact with the respondent, which may make some respondents uncomfortable. Interexaminer and intraexaminer reliability can be an issue with waist and hip circumferences because in obese subjects the identification of the waist can be subjective if not impossible (Heymsfield et al. 1998). Still, reliability of WC is high: interexaminer reliability is .960 and intraexaminer reliability is .972 (Mueller and Malina 1987). Another limitation is that circumferences are affected by variation in muscle and bone as well as fat (Heymsfield et al. 2004).

Body Composition

There are several methods for measuring body composition (in particular, body fat). One method is to use calipers to measure skinfold thickness; the rationale is that 70–90 percent of total adipose tissue is subcutaneous (Heymsfield et al. 1998). Measurement at only one site is a poor predictor of body fat, so measurements are generally made at multiple sites, such as triceps, biceps, subscapular (under the shoulder blade), and suprailiac (between the hip joint and bottom of the rib cage). The triceps and subscapular sites are the best places for taking such measurements because of their accessibility, ease of measurement, and high correlation with measures of total body fat (Heymsfield et al. 2004). Skinfold calipers, which range in price from \$95 to \$369. Maximum range of calipers is at least 48 mm and as high as 100 mm. The NHANES Continuous uses Holtain Skinfold Calipers.

Physical contact with the examiner in the process of skinfold measurements may make respondents uncomfortable. Another limitation is that for extremely obese people the examiner may be unable to find a recognizable fold of skin (Mueller et al. 1987; Heymsfield et al. 1998). As a result, skinfold thickness has a lower reliability (interexaminer reliability: .915, intraexaminer reliability: .937) than waist circumference (inter: .960, intra: .972) or hip circumference (inter: .970, intra: .976); still, the reliability of skinfold thickness is sufficiently high that it may be useful (Mueller et al.). Different brands of skinfold calipers may exert differing pressure and result in different readings, so it is recommended that a single brand of calipers be used within a study (Heymsfield et al.).

The steps for converting skinfold measurements into percentage of body fat are as follows. First, body density is predicted using tricep and subscapular skinfold thicknesses (Durnin and Womersley 1974). Second, percentage of body fat is computed using body density (Siri 1956; Durnin and Womersley). These equations can predict percent body fat with errors between 3.5 and 5.0 percent and a 95 percent confidence interval between plus or minus 7–10 percent (Heymsfield et al. 1998).

Aside from calipers, another option for measuring skinfold thickness is near infrared interactance, based on a handheld device that uses light to take a skinfold measurement at a particular site. Model, which cost between \$2,285 and \$4,245, can be calibrated for adults or children. These devices directly report body composition and also have the advantage of requiring less physical contact between examiner and respondent.

Another device that can directly calculate body composition is bioelectrical impedance analysis (BIA), which sends low levels of electricity through the body (NIH 1996). Because muscle is mostly water (a conductor) and fat is an insulator, the resistance of the body to electricity can be used to measure fatness.⁴ BIA devices can report percentage of body fat, total body fat, and total lean mass. Advanced devices can even report body composition by limb; e.g., fat mass and PBF for each arm and leg (people may not be symmetric in this regard). Prices range from \$795 to \$4,990 and devices can be leased instead of bought. First-generation BIA devices required the patient to lie down and for electrodes to be attached to various parts of the body. More recent BIA devices require only that the patient remove shoes and socks and stand on a metal platform that resembles a regular scale. Anecdotally, some individuals dislike having to remove their socks for the BIA. Maximum weight allowable ranges from 400 to 700 pounds. Some devices are designed to be portable. BIA is not recommended for pregnant women or people with

⁴Bioimpedance spectroscopy (BIS) is similar to BIA but uses a spectrum of frequencies to assess body composition.

pacemakers implanted⁵ (the NHANES III did not take BIA readings from them⁶). A limitation of BIA is that it relies on prediction equations to convert resistance into estimates of total body water or fat free mass (from which total body fat and PBF can be calculated); one must be careful to ensure that the population used to generate the prediction equation resembles the population to which the equation is being applied (Heymsfield et al. 1998). Another limitation is that BIA readings may be affected by factors such as time since last meal (Atkinson 2002), so for maximum comparability it is recommended that all BIA measurements be done at the same time of day.

A review of methods of assessing fatness compared the strengths and weaknesses of each (Heymsfield et al. 2004, Table 12). It rated BIA as superior to anthropometry (i.e., measurements of weight, skinfold thickness, or circumferences) in terms of accuracy, reproducibility, and requiring less technician training. It was rated as equal to anthropometrics in terms of cost to purchase and operate and transportability. BIA was also listed as appropriate for very obese adults, children, and the elderly.

In addition to these devices designed for field use, there are a variety of laboratory-based methods of assessing fatness that are generally considered to be more accurate than field-based methods. Because lab-based methods are not practical for the PSID, we do not describe them in detail here but we list some for future reference. Computed tomography (CT) is useful because it can distinguish visceral fat from subcutaneous fat and muscle from organs as well as determine bone thickness. Its disadvantage is that it uses doses of radiation to collect these data. Magnetic resonance imaging (MRI) has many of the same advantages of CT and without the disadvantage of using radiation. Dual-energy X-ray absorptiometry (DXA) uses X-rays to measure fat as well as muscle mass.⁷ Underwater weighing (UWW) has historically been regarded as the gold standard for measuring fatness (although DXA may now be even more accurate). Air displacement plethysmography (e.g., BodPod) is similar to UWW but the subject does not have to be placed in water. Many of these methods of measurement are impractical or infeasible for the severely obese.

An interesting new technology is the 3-D body scanner. This device cannot determine body composition but provides high-resolution 3-D images with precise body measurements. For example, the VITUS/smart 3D Body Scanner by Human Solutions takes 12 seconds to scan the body using eight cameras and four eye-safe lasers. These devices have been used by the airline industry to design seats for various body types, by health clubs to make before-and-after photos illustrating benefits of fitness regimens, and by some clothing manufacturers to make clothes tailored to a client's exact measurements. This is a laboratory-based device, so we do not recommend its use for the PSID, but for researchers interested in appearance and social science outcomes (such as marital status, discrimination, etc.) such data would be a boon. There are obvious concerns about confidentiality, because the image would be so detailed that one could recognize the respondent by sight, but data managers could consider removing data for the face.

⁵The NHANES III examination codebook stated that 41 people out of 18,037 (0.2%) had a pacemaker implanted.

⁶The NHANES III also excluded from BIA measurements those with amputations other than fingers or toes; artificial joints, pins plates, or other metal objects in the body; coronary stents or metal suture material in the heart.

⁷The NHANES, in its mobile examination van, now includes a DXA machine to measure bone mineral content and density as well as total body fat and lean muscle mass. We considered this to be currently impractical for PSID home visits, but as such devices become more portable and cheaper it may become feasible.

Genetic Predisposition

No single gene for human obesity has been definitively identified, but a 2005 update on the obesity gene map reported that 22 genes have been associated with obesity in at least five studies (Rankinen, Zuberi, Chagnon, et al. 2006). An important online resource is the Human Obesity Gene Map: <http://obesitygene.pbrc.edu/>, which reviews all markers, genes, and mutations associated or linked with obesity phenotypes. Having genetic information on respondents raises confidentiality issues and ethical issues (e.g., what if the PSID realizes that a respondent is predisposed to a terminal disease: should the respondent be notified?). See the articles in this special issue by Conley for a discussion of genetics and by Greely for a discussion of ethical and legal issues.

Blood Markers

Fat was once considered a passive store of energy but is now recognized as an endocrine organ that secretes hormones that can regulate appetite or do harm (Lazar 2005). Leptin is a protein produced by fat cells that, after entering the bloodstream, regulates appetite and stimulates energy expenditure. Studies have found that severely obese mice had defective leptin production (due to the obesity or “ob” gene) and after being treated with leptin lost weight (Pelleymounter, Cullen, Baker, Hecht et al. 1995). It is unclear whether the same relationship holds in humans, but in people leptin has been linked to cardiovascular disease (Sorensen, Echwald, and Holm 1996). Another protein released by fat cells is resistin, which has been linked to insulin resistance and onset of Type II diabetes (Lazar). Given the role of these hormones in appetite regulation and in causing obesity-related comorbidities, it may be worthwhile to measure their concentrations in the bloodstream. See the article by Goldman and Dowd in this special issue for a discussion of metabolic and cardiovascular biomeasures.

Value of Including Biomeasures of Fatness and Obesity in the PSID

In this section we explain why adding accurate measures of fatness to the PSID would be valuable for researchers.

Correlations between Different Measures

One might wonder whether having self-reported weight and height, allowing researchers to construct BMI, is a good enough measure of fatness and adequate predictor of outcomes of interest. This raises the question of how highly correlated are various measures of fatness and how highly correlated are the various measures of obesity, each based on one of those measures of fatness. The correlation of BMI with percentage of body fat ranges from 0.4 to 0.9 across studies (Heymsfield et al. 1998).⁸ Burkhauser and Cawley (2008) studied data from NHANES III and found that the correlation between obesity defined using BMI (calculated using measured weight and height) and obesity defined using PBF is relatively weak: .45 for males and .38 for females.

Clearly, extreme obesity is easy to identify with almost any measure of fatness; even though BMI cannot distinguish muscle from fat, a BMI of 50 cannot be due to muscularity

⁸Waist circumference is highly correlated with PBF with correlations above 0.90 in most populations (Heymsfield et al. 1998), but for women hip circumferences may have even slightly higher correlations with body fat (Heymsfield et al. 2004).

and clearly indicates obesity with something close to perfect accuracy. Thus, the value of more accurate measures of fatness comes from distinguishing the underweight, healthy weight, overweight, and obese, not from distinguishing the morbidly obese from all others.

Two recent studies confirmed that fatness measures can move independently of each other. Eloheide, Desmond, Thomas, Keith, and Allison (2007) documented that in the United States, WC rose faster between 1959 and 2004 than one would expect given changes in BMI over the same period. Burkhauser, Cawley, and Schmeiser (2009) found in the series of NHANES that obesity defined using skinfold thickness began rising one to two decades before obesity defined using BMI. This example illustrates how the measure of fatness chosen by researchers can have important consequences. Had obesity surveillance relied on a more accurate measure of fatness than BMI, or more broadly monitored multiple measures of fatness, the rise in U.S. obesity might have been detected, and public health responses begun, a decade or two earlier. Given the sensitivity of results to the choice of measure of fatness, Bouchard (2007) concluded that in experimental and clinical research settings it is always advisable to directly measure multiple metrics of adiposity.

Determining Who Is Truly Obese

An important reason for adding a more accurate measure of fatness to the PSID is that it will allow researchers to determine more accurately who is truly obese. Burkhauser and Cawley (2008) used NHANES III data on both BMI (calculated using measured weight and height) and PBF (calculated using BIA) to determine the accuracy of obesity defined using BMI to detect true obesity (defined using PBF). Controlling for the difference in thresholds for obesity for the two measures (more of the population is classified as obese by PBF than BMI) we find that obesity defined using BMI results in a 22.25 percent false positive rate among women and a 42.64 percent false positive rate among men. (BMI results in a higher false positive rate for men because they are more likely to be muscular: heavy but not sufficiently fat to be obese.) The rate of false negatives is 6.44 percent for women and 9.93 percent for men.

Moreover, the percentage of false positives varies by race and gender, with African Americans more likely than whites to be inaccurately classified as obese. The rate of false positives is 4.43 percent for white females but 10.56 percent for African American females. Among males, the rate of false positives is 7.77 percent for whites and 10.40 percent for African Americans. The fact that BMI mistakenly classifies as obese a higher proportion of African American men than white men may explain why Wildman et al. (2008) found that, when obesity is defined using BMI, obese African American men are significantly more likely than obese white men to be “metabolically healthy” (e.g., normal blood pressure and cholesterol levels).

When one uses the more accurate measure of PBF to classify individuals as obese, African American females are still more likely than white females to be obese, but the black-white gap in obesity rates falls by more than half among women (from 12.0 to 5.1 percentage points). When one uses BMI to define obesity, African American and white men have statistically indistinguishable rates of obesity, but when one defines obesity using PBF, the difference is statistically significant, with white men having an obesity rate that is 16.3 percentage points higher than that of African American men. In summary, the use of BMI creates a misleading impression of who is truly obese.

Another advantage of direct measures of fatness (PBF, WC, WHR, etc.) is that they tend to remain accurate at older ages. In contrast, BMI lacks validity as a measure of

fatness in the elderly, who tend to lose muscle mass with age and have greater concentration of their fat around their abdomen; as a result, BMI underestimates overweight and obesity in the elderly (Heymsfield et al. 1998).

Facilitate Research on the Causes of Obesity

Including in the PSID some accurate measures of fatness would allow social scientists and medical researchers to examine whether the rich set of social science variables included in the PSID are correlated with, are causes of, or are consequences of obesity. A growing literature has largely used surveys other than the PSID, such as the NHANES, NLSY, and BRFSS to examine whether factors such as income, neighborhood characteristics, family environment, and food prices contribute to obesity (e.g., D. Lakdawalla and Philipson 2002; Anderson, Butcher, and Levine 2003; Cutler, Glaeser, and Shapiro 2003; Chou, Grossman, and Saffer 2004; Cawley, Moran, and Simon Forthcoming). Adding more accurate measures of fatness to the PSID would allow researchers to exploit the longitudinal nature of the data to estimate change models, to exploit the household data to examine the influence of early family environment on future adult obesity, and in conjunction with the time diaries data, to study how allocation of time affects fatness and obesity. In general it is useful to have multiple measures of fatness when studying obesity (Bouchard 2007); for example, a review of programs to prevent childhood obesity recommends collecting data for multiple adiposity measures, including BMI, PBF, WC, etc. (Kropski, Keckley, and Jensen 2008, Table 5).

Better Predict Health and Mortality

In recent years a large number of studies have documented that measures of central adiposity (e.g., WC, WHR) are better predictors than BMI of heart attack and cardiovascular mortality. Inclusion of WC or WHR in the PSID would be helpful for two reasons: first, it would allow medical researchers and epidemiologists to better predict health outcomes and mortality in the PSID; and second, it will allow a wide range of researchers to better predict outcomes that are affected by health (such as labor market outcomes).

Though there is widespread agreement that WC or WHR performs better than BMI in predicting mortality, studies differ on whether WC or WHR is the best predictor. For example, in two recent studies both WC and WHR performed equally well in predicting mortality. Simpson, MacInnis, Peeters, Hopper, Giles, and English (2007) compared measures of adiposity in terms of their ability to predict all-cause mortality over 11 years. They found that for men, each of the measures predicted all-cause mortality, whereas for women the choice of fatness measure mattered: WC and WHR predicted all-cause mortality, but BMI, fat mass, and PBF did not. The authors recommended measuring WC and WHR in studies of the correlates of mortality. Pischon et al. (2008) tested whether central adiposity (i.e., WC or WHR) was predictive of mortality controlling for general adiposity (i.e., BMI). They found that both general and central adiposity are predictive of mortality and recommended that WC or WHR be used in combination with BMI in order to assess the risk of death.

Other studies concluded that WHR is preferable to WC. Zhang et al. (2007) found that WHR predicted mortality even controlling for BMI and concluded that it is important to measure fat distribution when assessing obesity-related health risk, and they supported the use of WHR as a way to improve risk assessment. Yusuf et al.

(2005) concluded that by a variety of standards, WHR and, to a lesser extent, WC better predicted heart attack than does BMI; an accompanying comment in *The Lancet* entitled “A Farewell to Body-Mass Index?” concluded that these findings represent “. . . the final nail in the casket for body-mass index as an independent cardiovascular risk factor . . .” (Kragelund and Omland 2005, pp. 1589–1590). Folsom, Kushi, Anderson, et al. (2000) also found that WHR was the best anthropometric predictor of total mortality.

Finally, some studies concluded that WC is preferable to WHR. Dobbelsteyn et al. (2001) found that WC predicted heart attack better than WHR or BMI. In 2008, Japan began monitoring adult obesity as part of a public health initiative to decrease health care costs, and the measure of fatness they chose to collect and monitor was WC because of its correlation with heart disease and diabetes (Onishi 2008). In the United States, an expert committee composed of a group of medical organizations (Klein et al. 2007) reviewed the literature and concluded that WC provides a unique indicator of body fat distribution that can indicate risk of obesity-related comorbidities independent of BMI and recommended that it be measured in clinical practice. Table 2 summarizes how the NIH (1998) classifies disease risk (for Type II diabetes, hypertension, and cardiovascular disease) based on WC in combination with BMI. By these NIH guidelines, a “high risk” waist circumference raises the risk of disease within the clinical weight classifications healthy weight, overweight, and obesity I (which corresponds to a BMI of at least 30 but less than 35). It does not raise disease risk within the classifications underweight, obesity II (which corresponds to a BMI of at least 35 but less than 40) or obesity III (which corresponds to a BMI greater than or equal to 40). Thus, even controlling for BMI, knowing WC increases one’s ability to classify individuals’ disease risks.

Table 2
Disease risk^a by BMI and waist circumference

Clinical classification	Weight		Waist circumference implies not high risk	Waist circumference ^b implies high risk
	BMI			
Underweight	<18.5	—	—	—
Healthy weight	18.5–24.9	—	—	^c
Overweight	25.0–29.9	Increased	High	Very high
Obesity I	30.0–34.9	High	Very high	Very high
Obesity II	35.0–39.9	Very high	Extremely high	Extremely high
Obesity III (extreme or morbid obesity)	≥40	Extremely high	Extremely high	Extremely high

Source: Adapted from table ES-4 on page xvii of NIH (1998).

Notes: ^aDisease risk is for Type II diabetes, hypertension, and cardiovascular disease.

^bWaist circumference implies person is at high risk if it exceeds 102 cm (40 inches) for men or 88 cm (35 inches) for women.

^cIndicates that the NIH states that increased waist circumference can also be a marker for increased risk even in persons of normal weight.

Better Predict Social Science Outcomes

The medical literature has for years been documenting the advantages of using more accurate measures of fatness than BMI. Social scientists continue to use BMI almost exclusively, largely because it is the only measure calculable in major social science surveys.

However, a few studies have examined whether more accurate measures of fatness correlate with social science outcomes of interest. For example, Burkhauser and Cawley (2008) examined the association of employment with BMI and total body fat (in kg) controlling for fat free mass (in kg). Previous studies on this topic used BMI as their measure of fatness (e.g., Averett and Korenman 1999; Cawley and Danziger 2005; Garcia and Quintana-Domeque 2007; Lundborg et al. 2007). After estimating models of employment using NHANES III data, we find that the use of more accurate measures of body composition makes a meaningful difference. For white females, BMI is negatively correlated with employment. However, when BMI is replaced by TBF and FFM, it is only TBF that is negatively correlated with employment; weight in the form of FFM has no association with employment. Thus, use of more accurate measures of body composition yields the insight that not all weight is equal; as one would expect based on the medical literature, fat is associated with worse outcomes, but more mass in the form of muscle (or bone, or water) is not. For white males, there is also a difference based on measure of fatness. Whereas BMI is not a significant predictor of employment, TBF is significantly and negatively correlated with employment. The coefficient on BMI represents a weighted average of the correlation of TBF and FFM and can obscure important relationships. Controlling for accurate measures of body composition can reveal these important relationships.

Much of the research on obesity and wages uses BMI as the measure of fatness (e.g., Averett and Korenman 1996; Cawley 2004). Johansson et al. (2009) compared the association of wages with a variety of anthropometric measures, including weight, height, fat mass, and waist circumference, in a data set of Finnish workers. They found that WC but not weight or fat mass was negatively correlated with wages for women. All measures of fatness are associated with a lower probability of employment for women.

In recent work we (Burkhauser et al. 2008) investigated which of the various measures of fatness contained in the NHANES III data best predicted application for Disability Insurance (determined using linkages to SSA data). Our results indicated that the measure of fatness that best predicts application for DI varies by race and gender. For white men, BMI consistently predicted future application for DI. For white women, almost all measures were consistently predictive of application. For black men, none predicted application. For black women, WC and WHR were the only significant predictors of DI application. This variation across race and gender suggests that the inclusion of multiple measures of fatness in social science surveys should be considered and that researchers examining the impact of fatness on social science outcomes should examine the robustness of their findings to alternative measures of fatness.

One area of research where more accurate measures of fatness have been used for years is the sociological literature on mate attractiveness, in which a woman's WHR has been used as a measure of her desirability (Singh and Young 1995; Braun and Bryan 2006). The rationale is that WHR is more highly correlated than overall body mass with onset of pubertal endocrinological activity and probability of conception (Singh and Young). Importantly, these studies reject the second half of the saying, "One can never be too rich or too thin": men do not prefer women who are so slender that they are tubular;

they prefer relatively slender women who have curvaceous hips and breasts. This literature confirms that with WHR, one can measure an important dimension of women's attractiveness to men.

What Additional Survey Questions Would Be Needed to Take Full Advantage of the Biomeasures?

A variety of questions added to the interview portion of the PSID would enhance the value of these more accurate measures of fatness and body composition. For example, the survey could ask what respondents are currently doing about their weight: trying to lose weight, doing nothing, or trying to gain weight. This would allow researchers to explore the triggers of dieting and the impact of dieting on outcomes controlling for fatness.

Controlling for actual fatness, perceived fatness could matter for self-esteem, so respondents could be asked: how would you describe your own weight: very overweight, somewhat overweight, about right, somewhat underweight, very underweight?

A series of questions from the BRFSS would also be complements: the frequency with which the respondent engages in vigorous, light, and strength-building exercise; frequency with which they consume specific types of food such as green salad, fruits and vegetables, soda pop, and fast food; and whether the respondent participates in specific unhealthy behaviors because of weight: e.g., takes over-the-counter weight loss pills, takes prescription anti-obesity drug, takes laxatives, vomits, etc.

Time diaries and dietary recall surveys (complete 24-hour recall, not just selected food frequencies) in each wave would allow researchers to examine the correlates of obesity and the causes and consequences of physical activity and a nutritious diet. Finally, an exciting new type of data collection is through pedometers or accelerometers, which measure the quantity and intensity of movement and thus provide objective measures of physical activity. For more details, see a 2005 supplement to the journal *Medicine and Science in Sports and Exercise* titled "Objective Monitoring of Physical Activity: Closing the Gaps in the Science of Accelerometry." The NHANES 2003–2004 wave included collection of accelerometer data.

Synergies with the PSID Structure

The longitudinal nature of the PSID, combined with the fact that it has been ongoing since 1968, would allow researchers to determine the early-life correlates of adult obesity. As multiple waves of data on obesity are collected, it would also allow researchers to determine whether there is a cumulative effect of obesity (wearing) on outcomes, distinct from the effect of contemporaneous obesity on those outcomes.

The genealogical structure of the data permits analysis of family correlations in weight status; see, for example, Davis et al. (2008). The genealogical structure also means that researchers can use one person's fatness/weight as an instrument for a biological relative's fatness/weight. A biological relative's fatness/weight is a valid instrument for fatness/weight because evidence supports that it is powerful (a large percentage of variance in fatness/weight is genetic in origin) and valid (the percentage of variance in fatness/weight due to shared household environment is typically too small to be detected). This type of instrumental variable model can be used to measure the causal effect of weight on labor market outcomes (e.g., employment, wages, and work limitations) and social outcomes (e.g., marriage, divorce). Previous papers to use this instrument include Cawley (2000, 2001, 2004), Lundborg et al. (2007), Brunello and D'Hombres (2007), and Kline and Tobias (2008).

In conjunction with the PSID Child Development Supplement time diaries, fatness measures would allow one to study how childhood fatness and obesity is related to the allocation of time and how changes in time correlate with changes in weight (Fertig, Glomm, and Tchernis 2009).

PSID geocodes could be used to merge in neighborhood characteristics, which would permit researchers to study the relationship between various aspects of the built environment (e.g., proximity to parks, safety, availability of grocery stores and fast food) in order to determine the neighborhood correlates of obesity. The Institute of Medicine has urged more research on the link between the built environment and obesity (Transportation Research Board [TRB] 2005).

In addition, the PSID includes a rich set of variables relating to labor market outcomes, socioeconomic status, marital history, and program participation that tend not to be available in datasets with rich information about fatness and obesity (e.g., the NHANES). If the PSID also included accurate measures of fatness, researchers could test more refined hypotheses about these outcomes than has previously been possible.

Given all these advantages of the PSID, if the PSID were to add rich information about fatness and obesity, it would likely become the preferred data set for those researching the family, environment, economic, and social causes of obesity and those studying the economic and social consequences of obesity.

Conclusion

There may not be a single measure of fatness that is best for every application; exactly which measure proves to be most predictive of any given outcome will likely depend upon how fatness or obesity affects the outcome of interest. For example, if one is studying health or outcomes affected by health, waist circumference might be most predictive. If one is studying marriage markets, a measure of appearance (such as waist-to-hip ratio for women) may be most relevant. If one is studying the wages of unskilled men, the most useful measure might be fat free mass (which includes muscle). Regardless of the outcome studied, research can be enriched by greater consideration of alternative measures of fatness and body composition.

For the purposes of the PSID, we recommend collecting waist circumference, because it measures central adiposity and is a better predictor of mortality (especially cardiovascular mortality) than BMI. We also recommend collecting percentage of body fat, total body fat, and fat free mass, all through bioelectrical impedance analysis,⁹ because they provide detailed information on body composition. Finally, we recommend that information be gathered about whether respondents share any of the markers, genes, and mutations identified as being associated with obesity in the obesity gene map. We recommend that the genetic data be collected once and the waist circumference and BIA data be collected at each wave.

If the fixed costs of collecting biomeasures in the home will be spent, it may make sense to collect data on additional measures of fatness and obesity, such as hip circumference (so one can calculate waist-to-hip ratio, a measure of attractiveness) and skinfold thickness (the near-infrared method may have higher reliability than calipers). If blood samples are being taken, it would be useful to measure levels of leptin and resistin, which would provide measures of the damage being done by excess fatness.

⁹We recommend BIA with the caveat that the most cost-effective and accurate method of measuring body composition will likely change over time.

All of these measures will vastly increase the value of the PSID for studying the causes and consequences of obesity. More broadly, their inclusion will allow all researchers to control for fatness and body composition in models for a host of diverse outcomes, thus avoiding omitted variables bias and increasing the models' predictive power and goodness of fit.

References

- Anderson, P. M., K. F. Butcher, and P. B. Levine. 2003. Maternal employment and overweight children. *J. Health Econ.* 22:477–504.
- Andreyeva, T., R. M. Puhl, and K. D. Brownell. 2008. Changes in perceived weight discrimination among Americans, 1995–1996 through 2004–2006. *Obesity* 16:1129–1134.
- Atkinson, R. L. 2002. Medical evaluation of the obese patient. In *Handbook of obesity treatment*, eds. T. A. Wadden and A. J. Stunkard, 173–185. New York: Guilford Press.
- Averett, S., and S. Korenman. 1996. The economic reality of the beauty myth. *J. Hum. Resour.* 31(2):304–330.
- Averett, S., and S. Korenman. 1999. Black-white differences in social and economic consequences of obesity. *Int. J. Obes.* 23:166–173.
- Bjorntorp, P. 2002. Definition and classification of obesity. In *Eating disorders and obesity: A comprehensive handbook* (2nd ed.), eds. C. G. Fairburn and K. D. Brownell, 377–381. New York: Guilford Press.
- Bouchard, C. 2007. BMI, fat mass, abdominal adiposity and visceral fat: Where is the “beef”? *Int. J. Obes.* 31:1552–1553.
- Bound, J., C. Brown, and N. Mathiowetz. 2002. Measurement error in survey data. In *Handbook of econometrics*, Vol. 5, eds. J. Heckman and E. Leamer, 3705–3843. New York: Springer-Verlag.
- Bowman, R. L., and J. L. DeLucia. 1992. Accuracy of self-reported weight: A meta-analysis. *Behav. Ther.* 23:637–655.
- Braun, M. F., and A. Bryan. 2006. Female waist-to-hip and male waist-to-shoulder ratios as determinants of romantic partner desirability. *J. Soc. Pers. Relat.* 23(5):805–819.
- Bray, G. A., C. Bouchard, and W. P. T. James. 1998. Definitions and proposed current classification of obesity. In *Handbook of obesity*, eds. G. A. Bray, C. Bouchard, and W. P. T. James, 31–40. New York: Marcel Dekker.
- Brunello, G., and B. D’Hombres. 2007. Does body weight affect wages? Evidence from Europe. *Econ. Hum. Biol.* 5:1–19.
- Burkhauser, R. V., and J. Cawley. 2008. Beyond BMI: The value of more accurate measures of fatness and obesity in social science research. *J. Health Econ.* 27(2):519–529.
- Burkhauser, R. V., J. Cawley, and M. D. Schmeiser. 2008. *The ability of various measures of fatness to predict application for disability insurance*. Cornell University working paper.
- Burkhauser, R. V., J. Cawley, and M. D. Schmeiser. 2009. The timing of the rise in U.S. obesity varies with measure of fatness. *Econ. Hum. Biol.* 7(3):307–318.
- Carmalt, J. H., J. Cawley, K. Joyner, and J. Sobal. 2008. Body weight and matching with a physically attractive partner. *J. Marriage Fam.* 70(5):1287–1296.
- Cawley, J. 2000. *Body weight and women’s labor market outcomes*. Cambridge: National Bureau of Economic Research Working Paper #7841.
- Cawley, J. 2001. Body weight and the dating and sexual behaviors of young adolescents. In *Social awakening: Adolescent behavior as adulthood approaches*, ed. R. T. Michael, 174–198. New York: Russell Sage.
- Cawley, J. 2004. The impact of obesity on wages. *J. Hum. Resour.* 39(2):451–474.
- Cawley, J., and S. Danziger. 2005. Morbid obesity and the transition from welfare to work. *J. Pol. Anal. Manag.* 24(4):727–743.
- Cawley, J., M. Grabka, and D. R. Lillard. 2005. A comparison of the relationship between obesity and earnings in the US and Germany. *J. Appl. Soc. Sci. Stud.* 125(1):119–129.

- Cawley, J., K. Joyner, and J. Sobal. 2006. Size matters: The influence of adolescents' weight and height on dating and sex. *Rationality and Society* 18(1):67–94.
- Cawley, J., J. Moran, and K. Simon. Forthcoming. The impact of income on the weight of elderly Americans. *Health Econ.*
- Cawley, J., J. A. Rizzo, and K. Haas. 2007. Occupation-specific absenteeism costs associated with obesity and morbid obesity. *J. Occup. Environ. Med.* 49(12):1317–1324.
- Chou, S.-Y., M. Grossman, and H. Saffer. 2004. An economic analysis of adult obesity: Results from the behavioral risk factor surveillance system. *J. Health Econ.* 23(3):565–587.
- Conley, D., and R. Glauber. 2007. Gender, body mass, and socioeconomic status: New evidence from the PSID. In *The economics of obesity, Vol. 17*, eds. K. Bolin and J. Cawley, 253–278. New York: Elsevier.
- Culyer, A. J., and J. P. Newhouse. 2000. *Handbook of health economics, Vols. 1A and 1B*. New York: Elsevier.
- Cutler, D. M., E. L. Glaeser, and J. M. Shapiro. 2003. Why have Americans become more obese? *J. Econ. Perspect.* 17(3):93–118.
- Davis, M. M., K. McGonagle, R. F. Schoeni, and F. Stafford. 2008. Grandparental and parental obesity influences on childhood overweight: Implications for primary care practice. *The J. Am. Board Fam. Med.* 21(6):549–554.
- Dobbelsteyn, C. J., M. R. Joffres, D. R. MacLean, and G. Flowerdew. 2001. A comparative evaluation of waist circumference, waist-to-hip ratio and body mass index as indicators of cardiovascular risk factors. The Canadian Heart Health Surveys. *Int. J. Obes. Relat. Metab. Disord.* 25(5):652–661.
- Durnin, J. V., and J. Womersley. 1974. Body fat assessed from total body density and its estimation from skinfold thickness: Measurements on 481 men and women aged from 16 to 72 years. *Br. J. Nutr.* 132:77–97.
- Elobeid, M. A., R. A. Desmond, O. Thomas, S. W. Keith, and D. B. Allison. 2007. Waist circumference values are increasing beyond those expected from BMI increases. *Obesity* 15(10):2380–2383.
- Engstrom, J. L., S. A. Paterson, A. Doherty, M. Trabulsi, and K. L. Speer. 2003. Accuracy of self-reported height and weight in women: An integrative review of the literature. *J. Midwifery Wom. Health* 48(5):338–345.
- Ferraro, K. F., Y. Su, R. J. Gretebeck, D. Black, and S. F. Bandylak. 2002. Body mass index and disability in adulthood: A 20-year panel study. *Am. J. Public Health.* 92(5):834–840.
- Fertig, A., G. Glomm, and R. Tchernis. 2009. The connection between maternal employment and childhood obesity: Inspecting the mechanisms. *Rev. Econ. Household.* 7:227–255.
- Finkelstein, E., I. Fiebelkorn, and G. Wang. 2003. National medical spending attributable to overweight and obesity: How much and who's paying? *Health Aff.* W3:219–216.
- Finkelstein, E., C. Fiebelkorn, and G. Wang. 2005. The costs of obesity among full-time employees. *Am. J. Health Promot.* 20:45–51.
- Flegal, K. M., B. I. Gaubard, D. F. Williamson, and M. H. Gail. 2007. Cause-specific excess deaths associated with underweight, overweight, and obesity. *JAMA* 298(17):2028–2037.
- Folsom, A. R., L. H. Kushi, K. E. Anderson, P. J. Mink, J. E. Olson, C. P. Hong, T. A. Sellers, et al. 2000. Associations of general and abdominal obesity with multiple health outcomes in older women: The Iowa Women's Health Study. *Arch. Intern. Med.* 160:2117–2128.
- Freedman, D. S., and G. Perry. 2000. Body composition and health status among children and adolescents. *Prev. Med.* 31(2, Part 2, Suppl.):S34–S53.
- Gallagher, D., M. Visser, D. Sepulveda, R. N. Pierson, T. Harris, and S. B. Heymsfield. 1996. How useful is body mass index for comparison of body fatness across age, sex, and ethnic groups? *Am. J. Epidemiol.* 143(3):228–239.
- Garcia, J., and C. Quintana-Domeque. 2007. Obesity, employment, and wages in Europe. *Adv. Health Econ. Health Serv. Res.* 17:187–217.
- Garn, S. M., W. R. Leonard, and V. M. Hawthorne. 1986. Three limitations of the body mass index. *Am. J. Clin. Nutr.* 44:996–997.

- Han, E., E. C. Norton, and S. C. Stearns. 2009. Weight and wages: Fat versus lean paychecks. *Health Econ.* 18(5):535–548.
- Haskins, K. M., and H. E. Ransford. 1999. The relationship between weight and career payoffs among women. *Socio. Forum* 14(2):295–318.
- Hedley, A. A., C. L. Ogden, C. L. Johnson, M. D. Carroll, L. R. Curtin, and K. M. Flegal. 2004. Overweight and obesity among U.S. children, adolescents, and adults, 1999–2002. *JAMA* 291(23):2847–2850.
- Heymsfield, S. B., W. Shen, Z. M. Wang, R. N. Baumgartner, D. B. Allison, and R. Ross. 1998. Evaluation of total and regional body composition. In *Handbook of obesity*, eds. G. A. Bray, C. Bouchard and W. P. T. James, 41–77. New York: Marcel Dekker.
- Heymsfield, S. B., R. N. Baumgartner, D. B. Allison, W. Shen, Z.-M. Wang, and R. Ross. 2004. Evaluation of total and regional adiposity. In *Handbook of obesity: Etiology and pathophysiology* (2nd ed.), eds. G. A. Bray and C. Bouchard, 33–79. New York: Marcel Dekker.
- Johansson, E., P. Böckerman, U. Kiiskinen, and M. Heliövaara. 2009. Obesity and labour market success in Finland: The difference between having a high BMI and being fat. *Econ. Hum. Biol.* 7(1):36–45.
- Jones, S. J., and E. A. Frongillo. 2006. The modifying effects of Food Stamp Program participation on the relation between food insecurity and weight change in women. *J. Nutr.* 136: 1091–1094.
- Klein, S., D. B. Allison, S. B. Heymsfield, D. E. Kelley, R. L. Leibel, C. Nonas, and R. Kahn. 2007. Waist circumference and cardiometabolic risk: A consensus statement from Shaping America's Health: Association for Weight Management and Obesity Prevention; NAASO, the Obesity Society; the American Society for Nutrition; and the American Diabetes Association. *Am. J. Clin. Nutr.* 85:1197–1202.
- Kline, B., and J. L. Tobias. 2008. The wages of BMI: Bayesian analysis of a skewed treatment-response model with nonparametric endogeneity. *J. Appl. Econometrics* 23:767–793.
- Kragelund, C., and T. Omland. 2005. A farewell to body-mass index? *Lancet* 366:1589–1591.
- Kropfski, J. A., P. H. Keckley, and G. L. Jensen. 2008. School-based obesity prevention programs: An evidence-based review. *Obesity* 16(5):1009–1018.
- Lakdawalla, D., and T. Philipson. 2002. *The growth of obesity and technological change: A theoretical and empirical examination*. Cambridge: NBER Working Paper #8946.
- Lakdawalla, D. N., J. Bhattacharya, and D. P. Goldman. 2004. Are the young becoming more disabled? *Health Aff.* 23(1):168–176.
- Lazar, M. A. 2005. How obesity causes diabetes: Not a tall tale. *Science* 307(5708):373–376.
- Lee, L.-F., and J. H. Sepanski. 1995. Estimation of linear and nonlinear errors-in-variables models using validation data. *J. Am. Stat. Assoc.* 90(429):130–140.
- Loh, E. S. 1993. The economic effects of physical appearance. *Soc. Sci. Q.* 74(2):420–438.
- Lumeng, J. C., K. Gannon, D. Appugliese, H. J. Cabral, and B. Zuckerman. 2005. Preschool child care and risk of overweight in 6- to 12-year-old children. *Int. J. Obes.* 29:60–66.
- Lundborg, P., K. Bolin, S. Hojgard, and B. Lindgren. 2007. Obesity and occupational attainment among the 50+ of Europe. *Adv. Health Econ. Health Serv. Res.* 17:219–251.
- McCarthy, H. D., T. J. Cole, T. Fry, S. A. Jebb, and A. M. Prentice. 2006. Body fat reference curves for children. *Int. J. Obes.* 30:598–602.
- McLean, R. A., and M. Moon. 1980. Health, obesity and earnings. *Am. J. Publ. Health* 70(9):1006–1009.
- Morris, S. 2007. The impact of obesity on employment. *Labour Econ.* 14:413–433.
- Mueller, W. H., and R. M. Malina. 1987. Relative reliability of circumferences and skinfolds as measures of body fat distribution. *Am. J. Phys. Anthropol.* 72:437–439.
- Narbro, K., G. Agren, E. Jonsson, B. Larsson, I. Naslund, H. Wedel, and L. Sjostrom. 1999. Sick leave and disability pension before and after treatment for obesity: A report from the Swedish Obese Subjects (SOS) study. *Int. J. Obes.* 23:619–624.
- National Institute of Diabetes and Digestive and Kidney Diseases, National Institutes of Health. 2006. Weight-control information network. Available online at: <http://win.niddk.nih.gov/publications/understanding.htm#distribution> (accessed March 7, 2007).

- National Institutes of Health. 1996. Bioelectrical impedance analysis in body composition measurement: National Institutes of Health technology assessment conference statement. *Am. J. Clin. Nutr.* 64(3S):524S–532S.
- National Institutes of Health. 1998. *Clinical guidelines on the identification, evaluation, and treatment of overweight and obesity in adults*. Washington, DC: NIH.
- Nieto-Garcia, F. J., T. L. Bush, and P. M. Keyl. 1990. Body mass definitions of obesity: Sensitivity and specificity using self-reported weight and height. *Epidemiology* 1(2):146–152.
- Ogden, C., M. D. Carroll, L. R. Curtin, M. A. McDowell, C. J. Tabak, and K. M. Flegal. 2006. Prevalence of overweight and obesity in the United States, 1999–2004. *JAMA* 295(13):1549–1555.
- Okoro, C. A., J. M. Hootman, T. W. Strine, L. S. Balluz, and A. H. Mokdad. 2004. Disability, arthritis, and body weight among adults 45 years and older. *Obes. Res.* 12(5):854–861.
- Onishi, N. 2008. Japan, seeking trim waists, measures millions. *New York Times* June 13. Available online at: <http://www.nytimes.com/2008/06/13/world/asia/13fat.html?ref=health>
- Pagan, J. A., and A. Davlia. 1997. Obesity, occupational attainment, and earnings. *Soc. Sci. Q.* 78(3):756–770.
- Paraponaris, A., B. Saliba, and B. Venelou. 2005. Obesity, weight status, and employability: Empirical evidence from the French National Survey. *Econ. Hum. Biol.* 3:241–258.
- Pelleymounter, M. A., M. J. Cullen, M. B. Baker, R. Hecht, D. Winters, T. Boone, and F. Collins. 1995. Effects of the obese gene product on body weight regulation in ob/ob mice. *Science* 269(5223):540–544.
- Pischon, T., H. Boeing, K. Hoffman, M. Bergmann, M. B. Schulze, K. Overvad, Y. T. van der Schouw. 2008. General and abdominal adiposity and risk of death in Europe. *N. Engl. J. Med.* 359:2105–2120.
- Pi-Sunyer, F. X. 2002. Medical complications of obesity in adults. In *Eating disorders and obesity: A comprehensive handbook* (2nd ed.), eds. C. G. Fairburn and K. D. Brownell, 467–472. New York: Guilford Press.
- Plankey, M. W., J. Stevens, K. M. Flegal, and P. F. Rust. 1997. Prediction equations do not eliminate systematic error in self-reported body mass index. *Obes. Res.* 5:308–314.
- Prentice, A. M., and S. A. Jebb. 2001. Beyond body mass index. *Obes. Rev.* 2(3):141–147.
- Pronk, N. P., M. J. Goodman, P. J. O'Connor, and B. C. Martinson. 1999. Relationship between modifiable health risks and short-term health care changes. *JAMA* 282:2235–2239.
- Puhl, R., and K. D. Brownell. 2001. Bias, discrimination and obesity. *Obes. Res.* 9(12):788–805.
- Puhl, R. M., and J. D. Latner. 2007. Stigma, obesity, and the health of the nation's children. *Psychol. Bull.* 133(4):557–580.
- Raebel, M. A., D. C. Malone, D. A. Conner, S. Xu, J. A. Porter, and F. A. Lanty. 2004. Health services use and health care costs of obese and nonobese individuals. *Arch. Intern. Med.* 164:2135–2140.
- Rankinen, T., A. Zuberi, Y. C. Chagnon, S. J. Weisnagel, G. Argyropoulos, B. Watts, L. Pérusse, et al. 2006. The human obesity gene map: The 2005 update. *Obesity* 14(4):529–644.
- Register, C. A., and D. R. Williams. 1990. Wage effects of obesity among young workers. *Soc. Sci. Quart.* 71(1): 130–141.
- Roehling, M. V. 1999. Weight-based discrimination in employment: Psychological and legal aspects. *Person. Psychol.* 52(4):969–1016.
- Rowland, M. L. 1989. Reporting bias in height and weight data. *Stat. Bull.* 70(2):2–11.
- Sarlio-Lahteenkorva, S., and E. Lahelma. 1999. The association of body mass index with social and economic disadvantage in women and men. *Int. J. Epidemiol.* 28(3):445–449.
- Simpson, J. A., R. J. MacInnis, A. Peeters, J. L. Hopper, G. G. Giles, and D. R. English. 2007. A comparison of adiposity measures as predictors of all-cause mortality: The Melbourne Collaborative Cohort Study. *Obesity* 15(4):994–1003.
- Singh, D., and R. K. Young. 1995. Body weight, waist-to-hip ratio, breasts and hips: Role in judgments of female attractiveness and desirability for relationships. *Ethology and Sociobiology* 16:483–507.
- Siri, W. E. 1956. Gross composition of the body. In *Advances in biological and medical physics*, Vol. 4, eds. J. H. Lawrence and C. A. Tobias, 239–280. New York: Academic Press.

- Smalley, K. J., A. N. Knerr, Z. V. Kendrick, J. A. Colliver, and O. E. Owen. 1990. Reassessment of body mass indices. *Am. J. Clin. Nutr.* 52:405–408.
- Snijder, M. G., M. Visser, J. M. Dekker, J. C. Seidell, T. Fuerst, F. Tylavsky, J. Cauley, et al. 2002. The prediction of visceral fat by dual-energy X-ray absorptiometry in the elderly: A comparison with computed tomography and anthropometry. *Int. J. Obes. Relat. Metab. Disord.* 26:984–993.
- Sobal, J. 2004. Sociological analysis of the stigmatization of obesity. In *A sociology of food and nutrition: The social appetite* (2nd ed.), eds. J. Germov and L. Williams, 383–402. Melbourne: John Wiley.
- Sorensen, T. I. A., S. M. Echwald, and J.-C. Holm. 1996. Leptin in obesity. *BMJ* 313:953–954.
- Snih, S. A., K. J. Ottenbacher, K. S. Markides, Y.-F. Kuo, K. Eschbach, and J. S. Goodwin. 2007. The effect of obesity on disability vs mortality in older Americans. *Arch. Intern. Med.* 167:774–780.
- Sturm, R., J. S. Ringel, and T. Andreyeva. 2004. Increasing obesity rates and disability trends. *Health Aff.* 23(2):199–206.
- Taubman, P. J. 1975. *Sources of inequality in earnings: Personal skills, random events, preferences toward risk and other occupational characteristics*. New York: American Elsevier Publishing Company.
- Transportation Research Board, Institute of Medicine. 2005. *Does the built environment influence physical activity? Examining the evidence*. TRB Special Report 282. Washington, DC: TRB.
- Trayhurn, P., and J. H. Beattie. 2001. Physiological role of adipose tissue: White adipose tissue as an endocrine and secretory organ. *Proc. Nutr. Soc.* 60:329–339.
- Tunceli, K., K. M. Li, and L. K. Williams. 2006. Long-term effects of obesity on employment and work limitations among US adults, 1986 to 1999. *Obesity* 14(9):1637–1646.
- U.S. Department of Health and Human Services. 2001. *The Surgeon General's call to action to prevent and decrease overweight and obesity*. Washington, DC: U.S. Government Printing Office.
- Wang, F., T. McDonald, J. Bender, B. Reffitt, A. Miller, and D. W. Edington. 2006. Association of healthcare costs with per unit body mass index increase. *J. Occup. Environ. Med.* 48:668–674.
- Wildman, R. P., P. Muntner, K. Reynolds, A. P. McGinn, S. Rajpathak, J. Wylie-Rosett, and M.-F. R. Sowers. 2008. The obese without cardiometabolic risk factor clustering and the normal weight with cardiometabolic risk factor clustering. *Arch. Intern. Med.* 168(15):1617–1624.
- Withers, R. T., J. LaForgia, R. K. Pillans, N. J. Shipp, B. E. Chatlerton, C. G. Schultz, and F. Leaney. 1998. Comparisons of two -, three -, and four - compartment models of body composition analysis in men and women. *J. Appl. Physiol.* 85:238–245.
- Yusuf, S., S. Hawken, S. Ounpuu, L. Bautista, M. G. Franzosi, P. Commerford, C. C. Lang, et al. 2005. Obesity and the risk of myocardial infarction in 27,000 participants from 52 countries: A case-control study. *Lancet* 366:1640–1649.
- Zhang, X., X.-O. Shu, G. Yan, H. Li, H. Cai, Y. T. Gao, and W. Zheng. 2007. Abdominal adiposity and mortality in Chinese women. *Arch. Intern. Med.* 167:886–892.